PREDICTING SELF-FULFILLING FINANCIAL CRISES

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MOTIVIATION & AIMS

Policymaking Problem:

Can policymakers predict financial market crises?

Problems of:

1. Predicting/postdicting financial crises (Danielsson et al. 2015; Frankel and Rose 1996; Leblang and Satyanath 2006; Frankel and Saravelos 2012; Minsky 1982)
2. Multiple equilibria in financial crises (Diamond and Dybvig 1983; Obstfeld 1994; Chang and Velasco 1998; Morris and Shin 20XX)

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Despite widespread agreement on existence of self-fulfilling crises, little analysis of implications for prediction.

Today: propose a model of prediction to explore consequences of coordination (2) for our ability to predict crises (1).

Empirically test the implications of the model with a new text-based measure of financial market stress.

THEORETICAL MODEL

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Crisis predictability is determined by the possible future states of the world. Hence, the more future states of the world, the less predictable a crisis is.

Core features of financial markets

1. Players have private information about their vulnerability to crises, i.e. liquidity demands, their willingness to cooperate.
2. Market sentiments vary across periods.
3. An observer uses behavior in time t to predict crises in period $t+1$.

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A two-player game of strategic complements with

1. Player types' σ_i drawn from single-peaked distribution F_σ, with support on the interval of $(\underline{\sigma}, \overline{\sigma})$.
2. Common shock representing market conditions to both players: κ.

NB: F_σ and κ are common knowledge. Only the realization of σ_i is private information.

Normalize the value of holding when the other player holds at 0, denote “sucker’s punishment” as $\alpha > 0$, and “first mover advantage” as $\beta > 0$. We then have:

Table: A Stag Hunt with Private Information and Common Shocks

		Player B	
		Hold	*Sell*
Player A	*Hold*	κ,κ	$-\alpha$, $\beta - \sigma_B$
	Sell	$\beta - \sigma_A$, $-\alpha$	$-\sigma_A$,$-\sigma_B$

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Sensible features of private σ_i and common shocks κ:

1. Larger σ_i increase the value of holding for each player.
2. Larger κ increase the value of holding for both players.

- Given common knowledge of F_σ, α, and β, strategies depend entirely on the values of σ_i and κ.
- The equilibrium is unique: players play a "cut-off" strategy where they sell iff $\sigma_i < \sigma^*$.

PREDICTIONS: AN OBSERVER

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Model the *Observer* as another player who predicts whether a crisis will take place in the future given the absence of a crisis today.

1. Nature draws σ_A, σ_B and reveals them to players A and B.
2. Nature draws κ_t from distribution F_κ and reveals it to A, B, and the Observer.
3. A and B play the game.
4. The Observer and A and B update their beliefs about the values of σ_A, σ_B conditional on what they observe.
5. The Observer predicts whether a financial crisis will occur given possible future realizations of the common shock κ_{t+1}.

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Proposition

If types are sparse and shocks are moderate, then larger common shocks κ_t *result in* larger $r(\kappa_t)$. *This implies a* higher variance in player types *in period 2 for any for any log-concave distribution* F_σ.

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Two mechanisms:

1. Shocks *screen types* by placing more bounds on $\sigma_{i,j}$.
2. Shocks *increase confidence* that each player's opponent is a strong type.

Implications:

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Extension:

- If shocks are positive enough, then multiple equilibria are possible, creating epistemic uncertainty.

EMPIRICAL TESTS

- GDP Growth (WDI 2015) & OECD (2015): higher growth $\implies$ better economic conditions.

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- $\frac{\text{LiquidAssets}}{\text{TotalAssets}}$ (Andrianova et al. 2015): Counterintuitive-ly, more liquid assets $\implies$ more stressed financial system (especially in developing countries).

Problems (1):

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- Many indicators of financial crises (e.g. Laeven & Valencia 2013; Reinhart & Rogoff 2010; Rosas 2009; Andrianova et al. 2015, Z-Scores) are annual.

Problems (2):

- Continuous sub-annual pricing measures (e.g stock market returns Danielsson 2015) have varying importance across countries/years.

SOLUTION: FINSTRESS

Gandrud & Hallerberg (2015)

Economist Intelligence Unit (EIU) monthly country reports are:

- comparable (from 2003) for 180+ countries,
- contemporaneous summaries of information in context.

EIU reports contain information about more than banking market conditions. So ...

Selected portions of texts based on keywords such as: *balance sheet*, *bank*, *credit*, and *finance*.

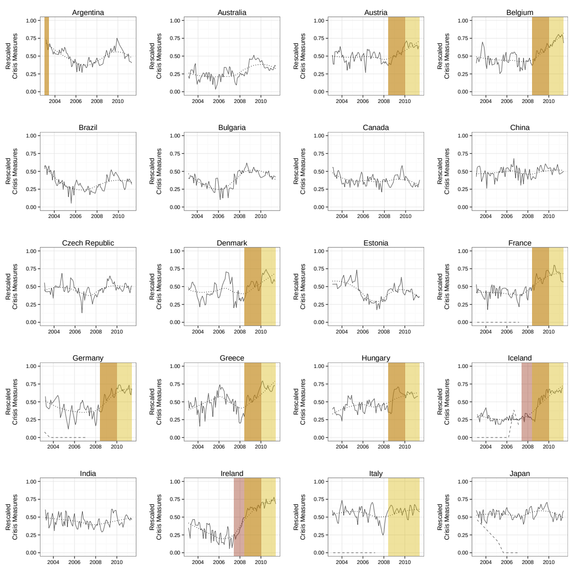
Results: 12,377 texts.

Use kernel principal component analysis (PCA) to summarise the texts on a more–less stressed scale [0, 1].

- Allows us to preserve word order, so that phrases like ‘expand credit’ and ‘slow credit’ distinguishable.
- Summary of qualitative assessments of quantitative data in context.

Ask Me about
Sub-string
Kernels,
Scaling

FINSTRESS (SELECTION)



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Use $\mathrm{Var}(\mathit{FinStress}_{t+1})$ as the dependent variable, where t is either a year or quarter.

Also…

MEASURING CURRENT CONDITIONS

- GDP Growth
- Stock Price Volatility
- $\log(\text{Impaired Loans})$
- $\frac{\text{LiquidAssets}}{\text{TotalAssets}}$
- $\text{FinStress}_{\bar{t}}$ Lower FinStress $\implies$ better financial market conditions.

RESULTS

Table: Regression result from predicting FinStress Variance using annual explanatory variable data (Full Sample)

	Dependent variable:				
	$\text{Var(FinStress)}_{year+1}$				
	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)
$\text{Var(FinStress)}_{year+0}$	0.014	−0.011	−0.083*	0.076**	0.054
	(0.029)	(0.030)	(0.047)	(0.038)	(0.035)
GDP Growth (%)	0.046**	0.028			
	(0.022)	(0.023)			
$\text{FinStress Mean}_{year}$		−5.347***	−6.263***		
		(1.299)	(2.404)		
Stock Price Volatility			−0.061***		
			(0.022)		
Impaired Loans (log)				−0.277	
				(0.196)	
Liquid Assets Ratio					0.026*
					(0.015)
Fixed Effects	y	y	y	y	y
Observations	1,349	1,349	599	833	939
R^2	0.004	0.018	0.044	0.009	0.007
Adjusted R^2	0.003	0.016	0.038	0.008	0.006
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table: Regression result from predicting FinStress Variance using annual explanatory variable data (OECD Sample)

	Dependent variable:				
	$Var(FinStress)_{year+1}$				
	OECD	OECD	OECD	OECD	OECD
	(1)	(2)	(3)	(4)	(5)
$Var(FinStress)_{year+0}$	0.036	−0.027	−0.048	0.052	0.089
	(0.068)	(0.070)	(0.072)	(0.077)	(0.074)
GDP Growth (%)	0.336***	0.207**			
	(0.083)	(0.090)			
FinStress $Mean_{year}$		−10.146***	−6.916*		
		(3.150)	(3.531)		
Stock Price Volatility			−0.144***		
			(0.039)		
Impaired Loans (log)				−1.636***	
				(0.530)	
Liquid Assets Ratio					0.043
					(0.055)
Fixed Effects	y	y	y	y	y
Observations	248	248	231	205	216
R^2	0.077	0.119	0.153	0.061	0.011
Adjusted R^2	0.067	0.103	0.132	0.052	0.009
Note:					*p<0.1; **p<0.05; ***p<0.01

Table: Regression result from predicting FinStress Variance using quarterly explanatory variable data (OECD only)

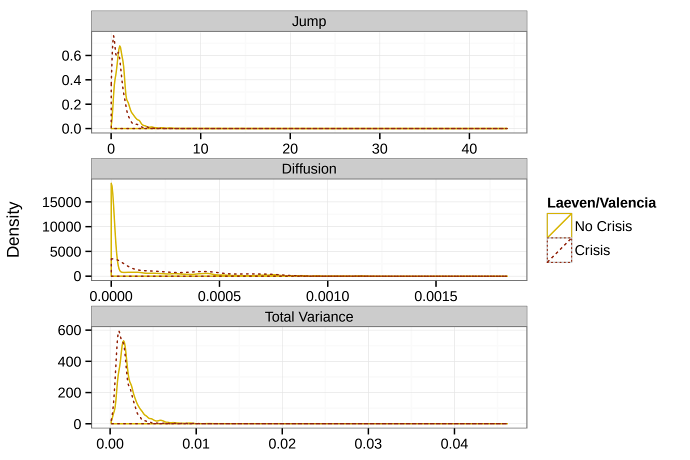
	Dependent variable:	
	$\text{Var(FinStress)}_{quarter+1}$	
	(1)	(2)
$\text{Var(FinStress)}_{quarter+0}$	0.090***	0.066**
	(0.027)	(0.027)
GDP Growth (%)	0.102***	0.043
	(0.027)	(0.029)
$\text{FinStress Mean}_{quarter+0}$		−5.569***
		(1.065)
Fixed Effects	y	y
Observations	1,237	1,237
R^2	0.023	0.045
Adjusted R^2	0.022	0.043
Note:	*p<0.1; **p<0.05; ***p<0.01	

Also examined FinStress with a Drift, Jump, Diffusion Approach often used in time-series forecasting.

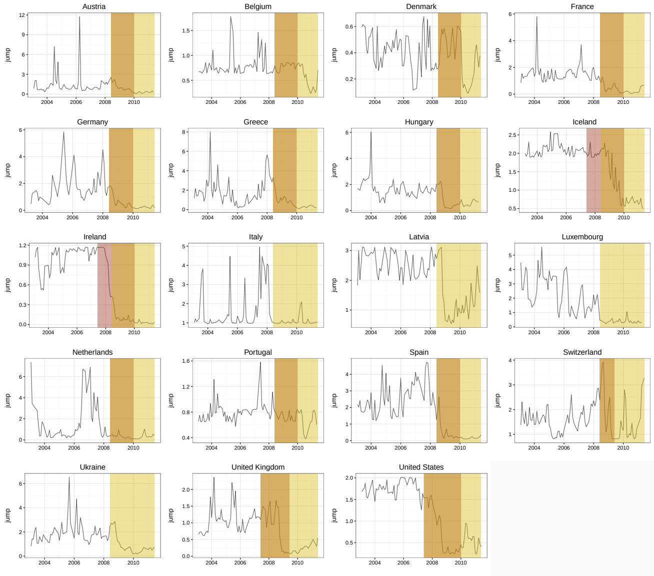
$$dx_t = f(x_t,\ \theta_t)dt + g(x_t,\ \theta_t)dw + dJ_t \tag{1}$$

- Drift $f(x_t,\ \theta_t)dt$: measures the local rate of change.
- Diffusion $g(x_t,\ \theta_t)dw$: small changes that happen at each time increment
- Jump dJ_t: large shocks that occur intermittently and are uncorrelated in time.

MORE JUMPS IN NON-CRISIS TIMES



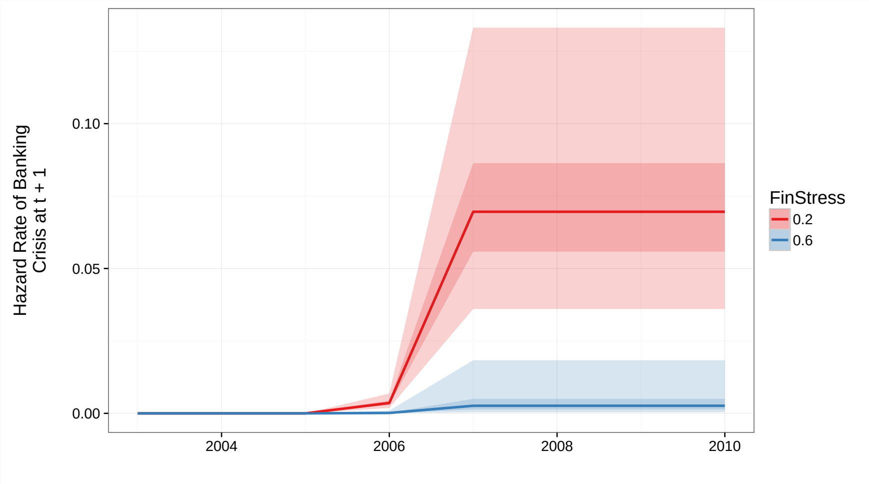
JUMPS FOR SELECTED COUNTRIES WITH CRISIS



OTHER HYPOTHESIS

Bad conditions are not indicative of future crises.

$t+0$ CONDITIONS PREDICT BANKING CRISES (LAEVEN/VALENCIA 2013)?



CONCLUSIONS

Central innovation: explicit model of the prediction problem during self-fulfilling crises:

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1. Observable economic conditions today help us to learn about players' types given their actions.
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1. Observable economic conditions today help us to learn about players' types given their actions.
2. However, we can learn less about crises in the future as the conditions today improve.

3. Empirically tested these implications with a new text-based measure of financial market stress.

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High-level contribution: a new model of why social scientists should be bad at predicting changes in equilibrium behavior when players coordinate with private information (cf. Kuran 1991). E.g. coups, revolutions.

FINANCIAL REGULATORY POLICY IMPLICATIONS

Given the findings in this paper, financial regulators should focus on trying to discern types (e.g. with stress tests), rather than focusing primarily on macro-economic conditions.